NEIGHBOURHOOD INFLUENCE AND SOCIAL ACCEPTANCE OF PV SYSTEMS IN RURAL DEVELOPING COMMUNITIES

Dr. Nicholas Nixon Opiyo
School of Computing, Engineering & Intelligent Systems
Ulster University, Magee Campus, Londonderry, BT48 7JL, UK
Email: N.Opiyo@Ulster.ac.uk

ABSTRACT: Knowledge of a new technology is necessary for a consumer to make an informed decision on its adoption, but this is difficult with nascent technologies such as solar home systems (SHS) where information is asymmetrical, with producers being in better positions to test the technology than consumers, contributing to their initial slow diffusions in new markets. In such cases, neighbourhood influence from early and independent adopters play important roles in increased future adoptions. In this work, impacts of neighbourhood influence and social pressure on temporal diffusion of SHS in a rural developing community are investigated. A survey is developed and carried out in Kendu Bay area of Kenya to gather information on how neighbourhood influence and social pressure impact on SHS installation decisions. Data from the survey is then used to inform an agent-based model (ABM) developed in NetLogo, to simulate impacts of neighbourhood influence radius and threshold, on temporal diffusion of SHS in a rural developing community. Results show that visibility of newly installed SHS leads to more installations that word-of-mouth alone. Results also show that increasing influence radius leads to exponential growth in SHS installations. For optimal SHS installations, a neighbourhood threshold of between 12.5% and 15% is required.

Keywords: Social Acceptance; Neighbourhood Influence; Visibility; Word-of-mouth

1 INTRODUCTION

Social acceptance is necessary for successful diffusion of a new technology within a given community, and this is especially so with solar microgeneration systems which impact on individuals' spaces both passively and actively [1-3]; an individual's willingness to participate in the microgeneration process through financial investment, provision of an installation site, or through behavioural change is important for successful uptake of such technologies [4]. Knowledge of a new technology is necessary for a consumer to make an informed decision on its adoption, but this is difficult with nascent technologies such as PV where information is asymmetrical, with producers being in better positions to test the technology than consumers, contributing to their initial slow diffusions in new markets [5-8].

Rogers' theory of diffusion of diffusion categorizes adopters based on temporal partitioning [9,10]. According to this theory, temporal diffusion of a new technology into a given market depends on its relative advantage, compatibility, ease of use, and social acceptance amongst other factors [9,10]. Innovators, the first 2.5% of adopters, influence future adopters through neighbourhood influence and social pressure (advertisements); different attitudes towards the new technology affect initial adoption rates, with more acceptances experienced with time after observations of the benefits of the new technology have been made [9,10]. On the other hand, Bass model allows different categories of adopters, namely 'innovators' and 'imitators', to exist simultaneously [10-12]. According to this model, if we assign a coefficient of innovation p to early adopter and a coefficient of imitation q to neighbourhood influence, the probability that a household deciding on PV installation actually adopts at time t is given by [10,11]

$$\big(p + qF(t)\big) \tag{1}$$

where $F(t)$ is the proportion of adopters at time t. Without neighbourhood influence, $p > 0, q = 0$, while without early adopters $p = 0, q > 0$.

The probability density function for a house that is deciding on PV installation at a time t is given by

$$f(t) = \big(p + qF(t)\big)\big(1 - F(t)\big) \tag{2}$$

And the corresponding cumulative density function is given by

$$F(t) = \frac{1 - exp(-(p+q)t)}{1 + \frac{q}{p} exp(-(p+q)t)} \tag{3}$$

Given a market potential factor m, cumulative adoption of PV at a time t is given by $F(t) \times m$. Coefficients p and q, and market factor m are considered environmental variables to account for the changing and unstable environment within which diffusion of a new technology occurs. Initial and independent adoption decisions are mainly influenced by perceived or measured costs, social pressures such as advertising campaigns, a level of awareness of the new technology, attitudes towards the new technology such as environmental concerns in case of PV, and social demographics such as education and income levels. These factors are captured in the coefficient of innovation p. Perceived and spoken (word-of-mouth) benefits of the new technology are captured in the coefficient of imitation q. Geographical factors such as location and demographics will determine the market saturation levels which are then captured in the market potential factor m.

Both Roger's theory and Bass model underscore neighbourhood influence as a major factor in social acceptance, and thus in diffusion of a new technology in a given area [13]. Bollinger and Gillingham argue that neighbourhood influence begins to play a more important role once early adopters have installed a new technology [14]; they infer that visibility of a new technology (PV installed on rooftops) coupled with word-of-mouth about benefits of the new technology leads to increased adoption within a given neighbourhood or sensing radius [14]. Weber and Rode researched on the impacts of observational learning, or visibility of a new technology, on adoption of PV installations, while ignoring the effects of social interactions or word-of-mouth [15]. They found that, even though visibility played an important role in PV diffusion, its effect was more localized to immediate neighbours thus to a small sensing radius [15].

It is difficult to model the impacts of different non-quantitative social aspects on the adoption of a new technology. However, a measurable parameter such as sensing-radius, the radius within which a household can 'sense' its neighbours, and neighbourhood-threshold, the minimum percentage of neighbours within a given sensing radius that must have adopted a new technology for a household to consider doing the same, can be modelled and varied to explore the impacts of such parameters on the adoption of a new technology. Robinson and Rai explore the importance of socio-economic data in modelling household PV adoption, using a GIS-integrated ABM model [16,17]. Their model uses empirical data to weigh the importance of different factors in PV adoption decisions, and to validate the models [16,17].

Whereas Robinson and Rai focused on a developed community in Texas, USA, this work uses survey gathered data to model how neighbourhood influence impacts on temporal diffusion of solar home systems (SHS) in a rural western Kenya, and by enlarge, similar rural developing communities, especially in sub-Saharan Africa. The model looks at how visibility of SHS, combined with word-of-mouth of their benefits, impact on their temporal diffusion within a given community. The model simulates the neighbourhood influence radius and neighbourhood threshold to determine optimal values for SHS diffusion.

2 METHODOLOGY

2.1 Survey Data Collection

A short survey was carried on SHS installed in Kendu Bay area of Kenya to gather information on reasons for such installations as detailed in [18]. Specifically, the survey sought to gather information on how neighbourhood influence and social pressure impacted on SHS installation decisions. The survey only targeted households with SHS. Before embarking on the survey, an ethics review process was carried out to ensure proper handling of gathered sensitive data. A comprehensive questionnaire was then prepared, taking into account the sensitivity of some of the questions, and local cultural inhibitions. Kendu Bay area of Kenya was chosen for the study because of an ongoing research in the area. The first survey was carried out in the area in 2015 as reported in [18]. Kendu Bay is a small rural community in Western Kenya, situated along the Lake Victoria, and near the equator. It has a population of about 31,000 people residing within three main locations of Pala, Gendia, and Kanam. The main economic activities are fishing and subsistence farming which occurs mainly near the shores of Lake Victoria and along a local permanent river called Awach, due to poor rainfall. The main source of employment is civil service with many people working for the local and national governments as administrators, clerks, teachers, police officers, or health officers. Other sources of employment are small scale businesses and consumer services, small scale manufacturing enterprises, and mining. Even though the government of Kenya considers Kendu Bay to be an electrified area (it defines an area as electrified if it is situated within 10 km of existing distribution lines), the truth is that only about 4% of the population are connected to the national grid due to high connections costs, very low power needs, and unreliability of the national grid [18]. The rest are dependent on small solar home systems, kerosene lanterns, or biofuels for lighting and cooking.

The survey was carried out by one person, the corresponding author, who is originally from the area, can speak the local language, and understands local cultural norms. A single surveyor also ensures uniformity in data collection, and enhances security and integrity of collected data. The survey was divided into three main sections: demographic information, technical information, and opinions and other comments. The demographic information section sought to identify the household size, education level of head of household, and income level. Technical information section sought to identify the size of the SHS installed, reasons behind the installation, how the installation was funded, problems with the installations, and any repairs/replacements to-date. The opinions and other comments section sought to obtain information on how neighbourhood influence and social pressure impacted on SHS installation decision. Specifically, this section looked at how observations, word-of-mouth, and advertisements impacted on SHS installation decisions.

The survey area was divided into three regions based on administrative boundaries, namely Gendia, Kanam, and Pala to ensure equal distribution of samples and to make it easier to manage the travel logistics. The three regions have the following approximate populations: 12,000, 10,000, and 9,000 and approximate corresponding households of 3,000, 2,500, and 2,000, respectively [19]. The surveyed households were those with visibly installed SHS and those that were nearest to the main roads. A total of 192 households with SHS were positively surveyed, representing about 23.2% of households with SHS in Kendu Bay area. Table 1 shows the population of each region and the corresponding survey household sample sizes, and inclusion probabilities. Inclusion probability in a region is given by dividing the region's households sample by its total households.

Region	Population	Households	Sample	Inclusion Probability
Gendia	12,000	3,000	88	0.029
Kanam	10,000	2,500	67	0.027
Pala	9,000	2,000	53	0.027
Kendu Bay (Total)	31,000	7,500	208	0.028

Table 1: Total Populations, Households, Samples, and Inclusion Probabilities

2.2 Agent-Based Model

An agent-based model (ABM) was developed in NetLogo as a tool for simulating impacts of neighbourhood influence on social acceptance and temporal diffusion of solar home systems in a rural developing community, with a focus on Kendu Bay area of Kenya. The model takes into account population distribution in the given area, solar microgeneration potential in the area [20], limitations of solar electricity microgeneration technologies, and decisions by human actors based on costs, neighbourhood influence, and electrification options in the area and simulates the interactions between these factors in order to capture the overall macro-effects of different micro-decisions. Survey data from Kendu Bay area of Kenya is used to inform the model [18]. Specifically, data on population distribution of the area, total SHS installations in the area, sizes of SHS installed in the area, reasons for SHS installations, neighbourhood influence on SHS installation decisions, impacts of costs on SHS installation decisions, and opinions on SHS systems are used to simulate temporal diffusion of SHS in the area.

A household without SHS would consider installing one if

$$LUCE_{PV} < C_{A/kWh} \tag{4}$$

where $C_{A/kWh}$ is avoided cost per kWh, i.e., the prevailing national grid electricity cost per kWh while $LUCE_{PV}$ is the levelized unit cost of delivered electricity and is given by

$$LUCE_{PV} = \frac{ALCC_{PV}}{W_p \times EHFS \times 365 \times CUF} \tag{5}$$

where W_p is the rated peak Watt capacity of the SHS panel and is based on a household's activity profile and power demand [20], $EHFS$ is the equivalent hours of full sunshine per day, CUF is the capacity utilization factor which incorporates non-utilization and outages of systems due to various reasons, and $ALCC_{PV}$ is the annualized life cycle cost which is calculated by summing up the cost of all of its individual components, i.e. the panel, battery, charge controller, and appliances multiplied by their respective capital recovery factors plus operations and maintenance costs. It is expressed as

$$\begin{aligned} ALCC_{PV} = (C_{0PV} \times CRF_{PV}) & \\ + (C_{0batt} \times CRF_{batt}) & \\ + (C_{0cc} \times CRF_{cc}) & \\ + \left(C_{0appl} \times CRF_{appl}\right) & \\ + C_{O\&M} & \end{aligned} \tag{6}$$

where C_{0PV} is the capital cost of the SHS panel, C_{0batt} is the capital cost of the battery, C_{0cc} is the capital cost of the charge controller, C_{0appl} is the capital cost of appliances, CRF_{PV}, CRF_{batt}, CRF_{cc}, and CRF_{appl} are the capital recovery factors of the SHS panel, the battery, the charge controller, and appliances, respectively, and $C_{O\&M}$ is the operations and maintenance cost.

Capital recovery factor (CRF) is calculated using the formula

$$CRF = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{7}$$

where i is the discount rate while n is the life of the particular component being considered.

SHS is actually installed by a household if

$$\frac{H_{PV/IR}}{H_{Total/IR}} \times 100 > T_{IR} \tag{8}$$

where $H_{PV/IR}$ is the number of households with PV within a given influence-radius (IR), $H_{Total/IR}$ is the total number of households within the same influence-radius, and T_{IR} is the neighbourhood threshold.

3 RESULTS AND DISCUSSION

3.1 Survey Results

A total of 208 households with visibly installed solar home systems (SHS) were approached. Out of these, 192 were characterised as positive respondents. The overall primary quality indicator is 92%. Table 2 shows response rates by region, and the corresponding quality indicators.

Region	Sample	Positive Respondents	Non-Respondents	Quality Indicator
Gendia	88	81	7	92%
Kanam	67	63	4	94%
Pala	53	48	5	91%
Kendu Bay (Total)	208	192	16	92%

Table 2: Response Rates by Region

According to respondents, the main reasons for SHS installations was the need for better quality lighting than from kerosene lanterns of biomass. This was then followed by need to independently charge one's own mobile phones. Some correspondents gave mobile phone charging as the main reason for installation, followed by need for quality lighting. Since 97% of the systems installed were below 20Wp capacity, they could hardly provide power beyond the above two functions. However, some people still managed to get additional use for their systems including: offering home-based mobile charging services and powering small radios. Table 3 summarizes the above information.

Main Reasons for SHS Installations	Households	Percentage (%)
Lighting	169	88
Phone Charging	21	11
Other Uses	2	<1

Table 3: Main Reasons for SHS Installations

Out of the 192 positive correspondents, 18 were characterised as early adopters, having installed SHS without neighbourhood influence or social pressure, but purely for better quality lighting and to charge own mobile phones. The remaining 174 were classified as imitators, having installed SHS due to influence from other factors such as seeing neighbours/relatives with one, hearing about neighbours/with one, visual advertisements (billboards, posters and flyers), radio advertisements, and TV advertisements. Results show that neighbourhood influence played a larger role in SHS installation decisions than did advertisements. This is because of the high esteem status that SHS brings with it, in addition to obvious electrification advantages. Having a visibly installed SHS in the village brings with it a high status of financial stability and ability. It also brings with it a bragging right at the community gossip table in the village market. Advertisements also played major roles in SHS installation decisions, especially visual advertisements (billboards/posters and TV); people who saw the SHS and their benefits were more like to install them than those who just heard about them on radio. Table 4 summarizes the above information.

Influencing Factors	**Households**	**Percentage (%)**
Neighbourhood Influence	95	50
Advertisements	79	41
Early Adopters	18	9

Table 4: Factors Influencing SHS Installations

Under neighbourhood influence, 71 households decided to install SHS after seeing their neighbours with the same. Another 24 installed SHS after hearing about them and their potential benefits from their neighbours. Under advertisements, 34 households installed SHS after seeing them on billboards, posters, or flyers while 26 households installed SHS after seeing them in TV ads. Another 19 installed SHS after hearing about them in radio ads. Visibility of SHS, either through neighbours or advertisements therefore contributed more to their installation decisions, than hearing about them. In total, 131 households, or 68%, installed SHS after seeing them while 43 households, or 23% installed SHS after hearing about them and their benefits. Households are therefore 3 times more like to install SHS after seeing them from neighbours or advertisements, than after hearing about them. Table 5 below summarizes the above information.

<table>
<tr><th colspan="2">Influencing Factors</th><th colspan="2">Households</th><th colspan="2">Percentage (%)</th></tr>
<tr><td colspan="2">Early Adopters</td><td colspan="2">18</td><td colspan="2">9</td></tr>
<tr><td>Seen from neighbours</td><td rowspan="3">Seen SHS</td><td>71</td><td rowspan="3">Total = 131</td><td>37</td><td rowspan="3">Total = 68</td></tr>
<tr><td>Billboards/Posters/Flyers</td><td>34</td><td>18</td></tr>
<tr><td>TV Ads</td><td>26</td><td>14</td></tr>
<tr><td>Heard from neighbours</td><td rowspan="2">Heard of SHS</td><td>24</td><td rowspan="2">Total = 43</td><td>12</td><td rowspan="2">Total = 23</td></tr>
<tr><td>Radio Ads</td><td>19</td><td>10</td></tr>
</table>

Table 5: Comparison of Different Influencing Factors on SHS Installations

All of the 18 early adopters paid for their systems in cash up-front at costs of between US$ 175 for a 10Wp system with battery, USB phone battery charger, and 3 LED lamps and US$300 for a 20Wp system with battery, USB phone battery charger, and 3 LED lamps. The late adopters funded their systems through cash payments, pay-as-you-go (PAYG) mobile platforms, and hire purchase. Specifically, 4 households paid for their systems in cash up-front, 61 paid for their systems through hire-purchase, while 109 paid for their systems through PAYG mobile platforms. The hire purchase is offered to civil servants and prominent local residents (easily identifiable) by large retail shops, locally known as wholesalers. The African Retail Traders (ART) exclusively offers hire purchase services to civil servants at interest free terms. The buyers pay for the system in 6 equal monthly instalments. Other retailers offering hire purchase services have modelled their terms around the ART system. However, many rural households are still too poor to be credit worthy. For these household, PAYG mobile money platforms offer the reprieve. They pay for their system in between 1-3 years. Payments are usually made weekly, fortnightly, or monthly, with top-ups made to a card that is then inserted into a meter. If one misses a top-up, the PAYG company has a legal right to collect the SHS. However, even though the PAYG systems offer electrification paths to the poorest in the community, their path to electrification of also the most expensive. A system that costs US$175 in cash purchase will cost about US$500 when fully paid through PAYG. A random market sampling of the two most famous PAYG companies in the area showed that they sell electricity at a cost of about US$:2.82 – US$:3.45/kWh, depending on the size of the system, and the length of the payment. This is way above the national grid price of US$0.20/kWh. So, even though a weekly or monthly payment may look less that what one spends on kerosene or biofuels during similar periods, better and more affordable microcredit facilities are still lacking, to enable more households to access electricity in rural sub-Saharan Africa. Table 6 below summarizes the above information.

SHS Payment Method	**Households**	**Percentage (%)**
Pay-as-You-Go (PAYG)	109	57
Hire Purchase	61	32
Cash Upfront	22	11

Table 6: Comparison of Impacts of Different SHS Payments Methods on SHS Installations

3.2 Simulations Results

Data from the survey is used to inform the agent-based model from which neighbourhood influence-radius and neighbourhood threshold are used to simulate impacts of neighbourhood influence and social pressure on temporal diffusion of SHS within a similar developing community. Figure 1 below shows a view of the world after 25 years. The landscape is coloured green with the lighter areas being hill tops. Black houses are those that are unelectrified. Houses deciding on installing SHS are coloured white while those that have installed SHS are coloured yellow.

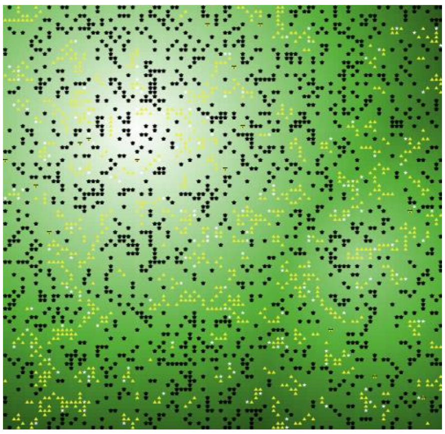

Fig. 1: A View of the World after Simulations after 25 Years

Figure 2 shows a plot of households with SHS after 25 years. At year zero (2015), there were about 347 households with SHS installed in Kendu Bay area [18]. Now (2018), a new survey shows that there are about 828 households with SHS. Simulation results show that after 25 years there will be about 4,325 households with SHS, representing 44.1% of all households. This massive growth is attributable to many factors with the main ones being a surge in availability of microcredit facilities tailored for such purchases, increasing neighbourhood influence and social pressure due to increasing SHS installations, and increasing awareness of the socio-economic benefits of SHS systems. Other possible attributes include falling PV costs, increasing household incomes, and increasing PV efficiencies.

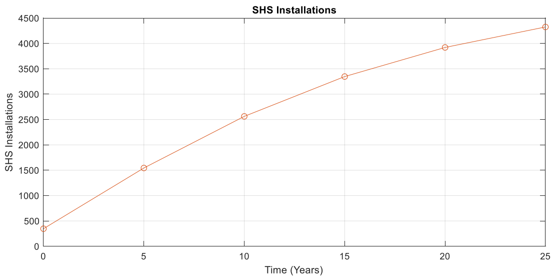

Fig. 2: SHS Installations Over 25 Years

3.2.1 Influence-Radius (IR)

Influence-radius is the radius within which a household influences, or is influenced by, its neighbours. The default radius is set at 1 km based on population distribution and terrain of Kendu Bay area. The sparseness of the rural population makes such a radius meaningful, as most households live within 5 km of a common village market and a permanent river or water source (lake Victoria in this case). The model simulates how a household's increasing influence-radius (IR) impacts on its SHS installation decision. As shown in figure 3 below, with a default IR of 1km, 828 households have installed SHS now. This number increases exponentially with increasing IR, with simulated data showing that 2,189 households would have installed SHS by now if the IR was set at 5 km.

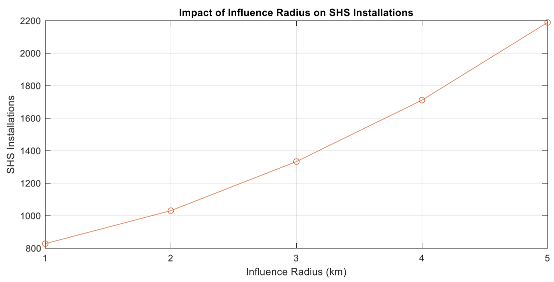

Fig. 3: Impact of Influence Radius on SHS Installations

Figure 4 compares impacts of different IR on temporal diffusion of SHS within Kendu Bay area. With a default IR of 1 km, 4,325 households would have installed SHS after 25 years. This figure increases with increasing IR, with an IR of 5 km showing 8,999 SHS installations after 25 years, more than twice the value with 1 km. Increasing neighbourhood influence radius therefore leads to exponential increases in SHS installations.

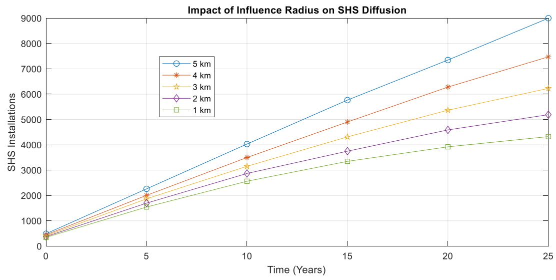

Fig. 4: Comparison of SHS Installations Over 25 Years with Different Influence Radii

3.2.2 Neighbourhood Threshold

Neighbourhood threshold is the minimum percentage of neighbours within a given IR that must have installed SHS for a household to consider doing the same. It is a measure of social pressure, and how this pushes households to install SHS, as increasing number of neighbours do so. It also shows the tipping point, above which SHS installations begin to fall. Figure 5 shows SHS installations versus increasing neighbourhood threshold. With a default threshold of 5%, 828 households have installed SHS now. This logarithmically increases to an optimum of about 1,089 installations with a threshold of between 12.5% and 15%. Installations then fall rapidly with increasing neighbourhood threshold, with thresholds above 20% leading to lower and lower installations.

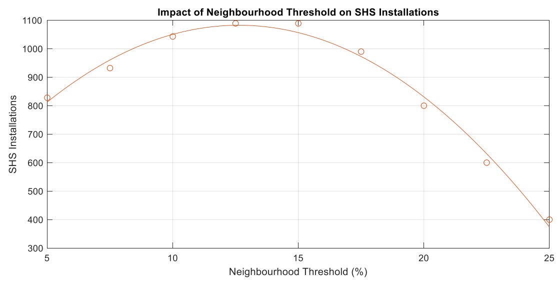

Fig. 5: Impact of Neighbourhood Threshold on SHS Installations

Figure 6 compares impacts of different neighbourhood thresholds on temporal diffusion of SHS within Kendu Bay area. With a default threshold of 5%, 4,325 households would have installed SHS after 25 years. The optimum threshold is between 12.% and 15% where 5,666 households would have installed SHS after 25 years. On the other hand, thresholds above 20% lead to lower installations, with a threshold of 25% leading to 2,076 installations after 25 years. If neighbourhood threshold was factored into SHS installation decisions, thresholds of between 12.5 and 15% would be recommended.

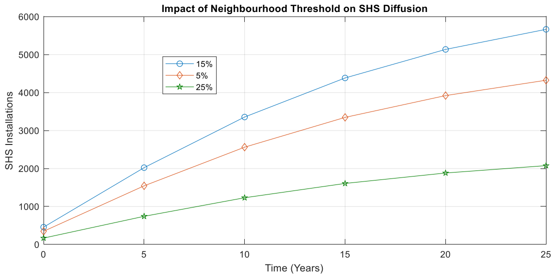

Fig. 6: Comparison of SHS Installations Over 25 Years with Different Neighbourhood Thresholds

4 CONCLUSION

In this work an agent-based model (ABM) is developed in NetLogo and used to simulate how neighbourhood influence and social pressure, modelled as sensing radius and neighbourhood threshold, impact on temporal diffusion of solar home systems (SHS) in a rural developing community. A survey is developed and carried out in Kendu Bay area of Kenya to gather data to inform the ABM. Results show that increasing neighbourhood influence leads to increasing SHS installations within a given rural developing community. Neighbourhood influence comes in forms visibility of installed SHS, word-of-mouth from neighbours, family, friends, etc., and social pressure through advertisements etc. Visibility of SHS, especially through neighbours that have installed the same, stimulate SHS installations within the same neighbourhood radius because neighbours see the benefits of the systems first hand and long for the benefits. Such benefits include improved lighting quality at night, improved sense of security, and ability to charge mobile phones. Those with visibly installed SHS are seen to have achieved a certain social status within the society, and this drives other households to install SHS so as to achieve the same status. In addition to visibility of installed SHS, neighbourhood influence is also achieved through word-of-mouth. Results show that households are likely to install SHS if their relatives, neighbours, friends, or colleagues have done the same.

Specifically, results show that increasing of a household's neighbourhood influence radius, the radius within which a household can be influence by its neighbours, leads to exponential increases in SHS installations. This is because as more households install SHS within a given sensing radius (neighbourhood), a threshold is reached where a household begins to take notice. With increasing observations, greater communication via visibility, word-of-mouth, and elevated social status of those with SHS, a household is increasingly pressured to consider doing the same. This leads to more SHS installations within a given area as a result of greater neighbourhood influence. Potential methods to increase neighbourhood influence within a given community include increased advertisements through posters, billboards, or even the local radio and TV channels, community outreach through chiefs and other local leaders, roof-top mounting of PV systems to increased external visibility, and compensated referrals, as is currently being done by ART in Kendu Bay.

4.1 References

1. Sauter, R., Watson, J., *Strategies for the Deployment of Micro-Generation Implications for Social Acceptance*, Energy Policy **35**:2770-2779, 2007
2. Semadeni, M., Hansmann, R., Flueeler, T., *Public Attitudes in Relation to Risk and Novelty of Future Energy Options*, Energy & Environment **15**:755-777, 2004
3. Kaldellis, J., *Social Attitude Towards Wind Energy Applications in Greece*, Energy Policy **33**:595-602, 2005
4. Faiers, A., Neame, C., *Consumer Attitudes Towards Domestic Solar Power Systems*, Energy Policy **34**:1797-1806, 2006
5. Young, H., *Innovation Diffusion in Heterogeneous Populations: Contagion, Social Influence, and Social Learning*, The American Economic Review **99:** 1899-1924, 2009
6. Bollinger, B., Gillingham, K., *Peer Effects in the Diffusion of Solar Photovoltaic Panels*, Marketing Science **31:** 800-812, 2012
7. Narayanan, S., Nair, H., *Estimating Causal Installed-Base Effects: A Bias-Correction Approach*, November 2, 2012
8. Rai, V., Robinson, S., *Effective Information Channels for Reducing Costs of Environmentally Friendly Technologies: Evidence from Residential PV Markets*, Environmental Research Letters **8:** 014044, 2013
9. Rogers, E., *Diffusion of Innovations*, 5th edn, Free Press, New York, NY, 2010.
10. Reeves, D., Rai, V., Margolis, R., *Evolution of Consumer Information Preferences with Market Maturity in Solar PV Adoption*, Environ. Res. Lett. **12:** 07411, 2017
11. Bass, F., *A New Product Growth for Model Consumer Durables*, Manage. Sci. **15:** 215-27, 1969
12. Mahajan, V., Muller, E., Srivastava, R., Determination *of Adopter Categories by Using Innovation Diffusion Models*, J. Market. Res. **27:** 37-50, 1990
13. Dong, C., Sigrin, B., Brinkman, G., *Forecasting Residential Solar Photovoltaic Deployment in California*, Technol. Forecast. Soc. **117:** 251–65, 2016
14. Bollinger, B., Gillingham, K., *Peer Effects in the Diffusion of Solar Photovoltaic Panels*, Marketing Science **31:** 800-812, 2012
15. Rode, J., Weber, A., *Knowledge Does Not Fall Far from the Tree - A Case Study on the Diffusion of Solar Cells in Germany*, ERSA Conference Papers ersa11p497, European Regional Science Association, 2011
16. Robinson, S., Rai, V., *Determinants of Spatio-Temporal Patterns of Energy Technology Adoption: An Agent-Based Modelling Approach*, Applied Energy **151:** 273-284, 2015
17. Rai, V., Robinson, S., *Agent-based Modelling of Energy Technology Adoption: Empirical Integration of Social, Behavioural, Economic, and Environmental Factors*, Environ. Model. Softw., **70:** 163-177, 2015
18. Opiyo, N., *A Survey Informed PV-Based Cost-Effective Electrification Options for Rural Sub-Saharan Africa*, Energy Policy

91: 1-11, 2016
19. Central Bureau of Statistics, Office of the Vice President, and Ministry of Planning and National Development, *Economic Survey*, Nairobi, 2011
20. Opiyo, N., *Modelling PV-Based Communal Grids Potential for Rural Western Kenya*, Sustainable Energy, Grids and Networks **4:** 54-61, 2015.